



LOGICAL CLOCKS

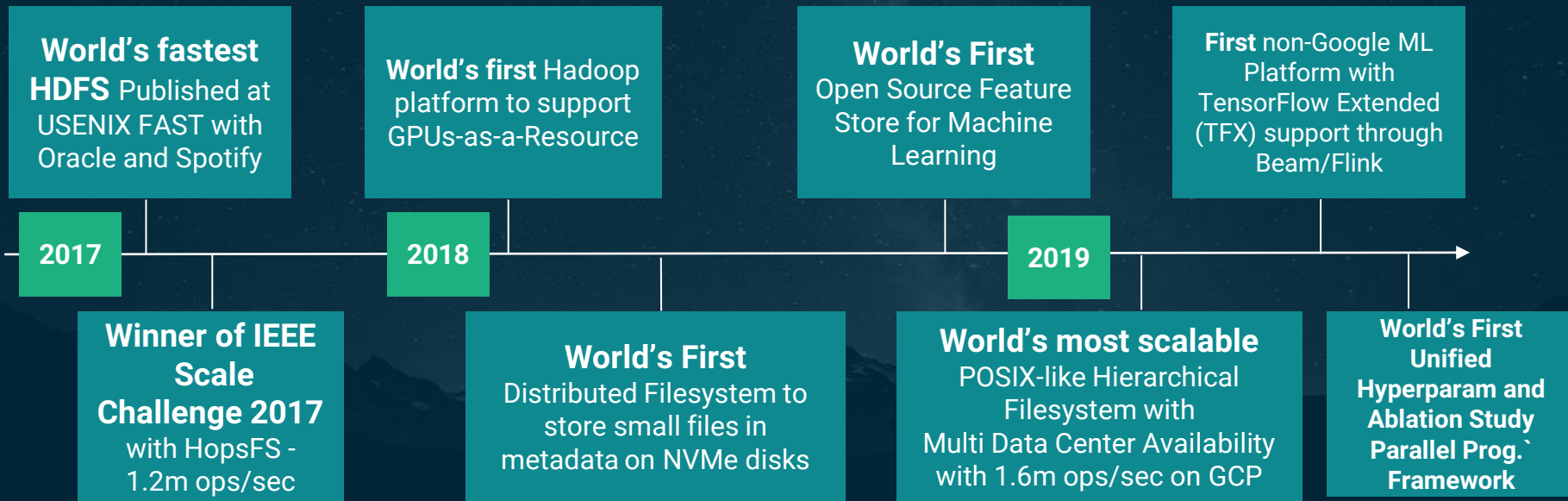
Hopsworks



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Nov 2019

Hopsworks Technical Milestones



"If you're working with big data and Hadoop, **this one paper could repay your investment** in the Morning Paper many times over.... **HopsFS is a huge win.**"

- Adrian Colyer, *The Morning Paper*

0. Slides:

<http://hops.io/id2223.pdf>

1. Register for an account at:

www.hops.site

2. Follow the Instructions here:

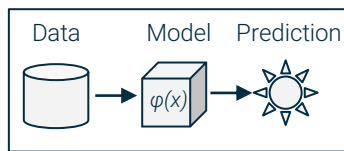
<https://bit.ly/2UEixTr>

3. Getting started Videos

<https://bit.ly/2NnbKgu>

Hopsworks hides the Complexity of Deep Learning

Hopsworks
Feature Store



Hopsworks
REST API

[Adapted from Schulley et al "Technical Debt of ML"]

Hopsworks

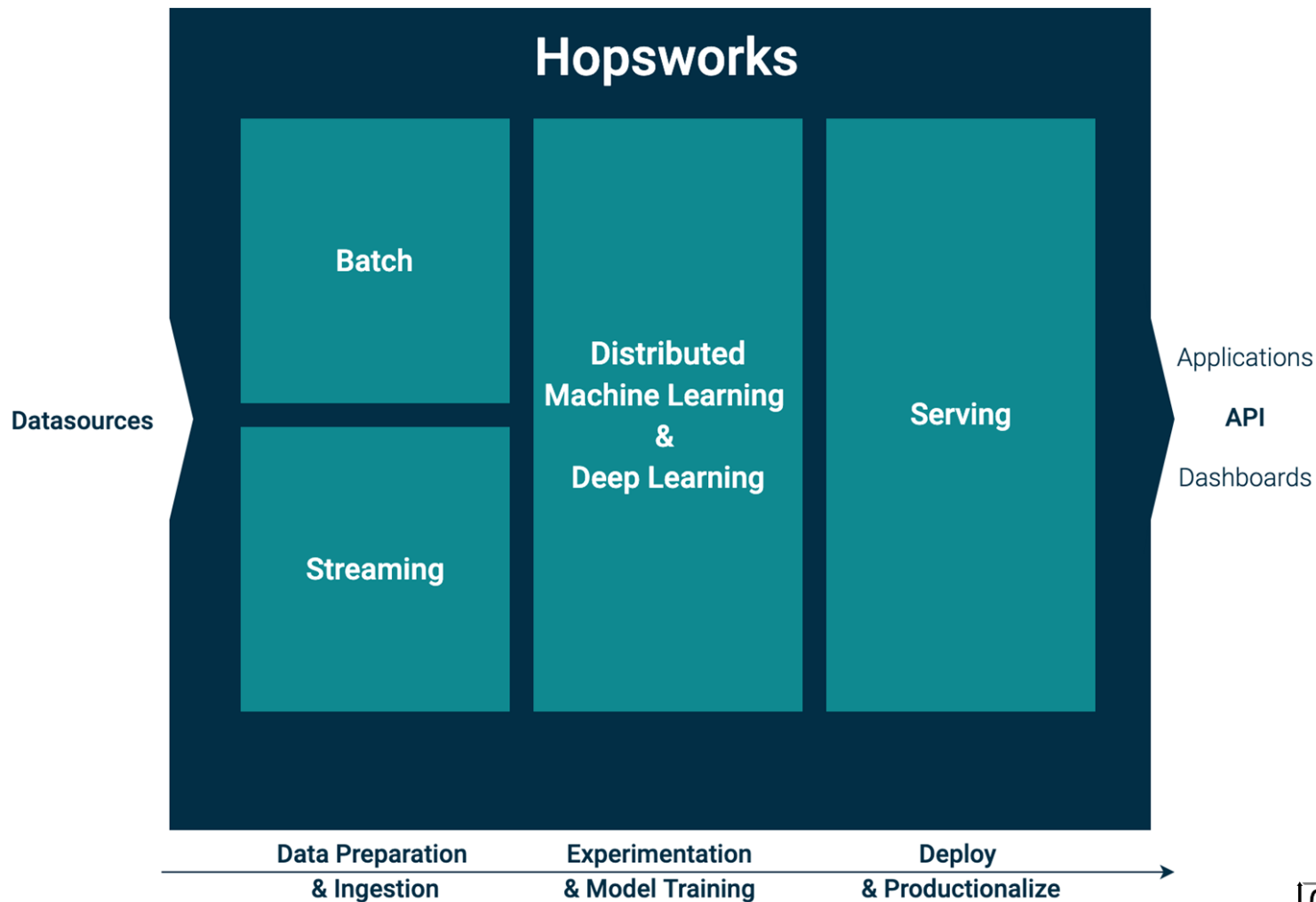
The Platform for Data Intensive AI
-
Machine Learning, Deep Learning &
Model serving

Datasources

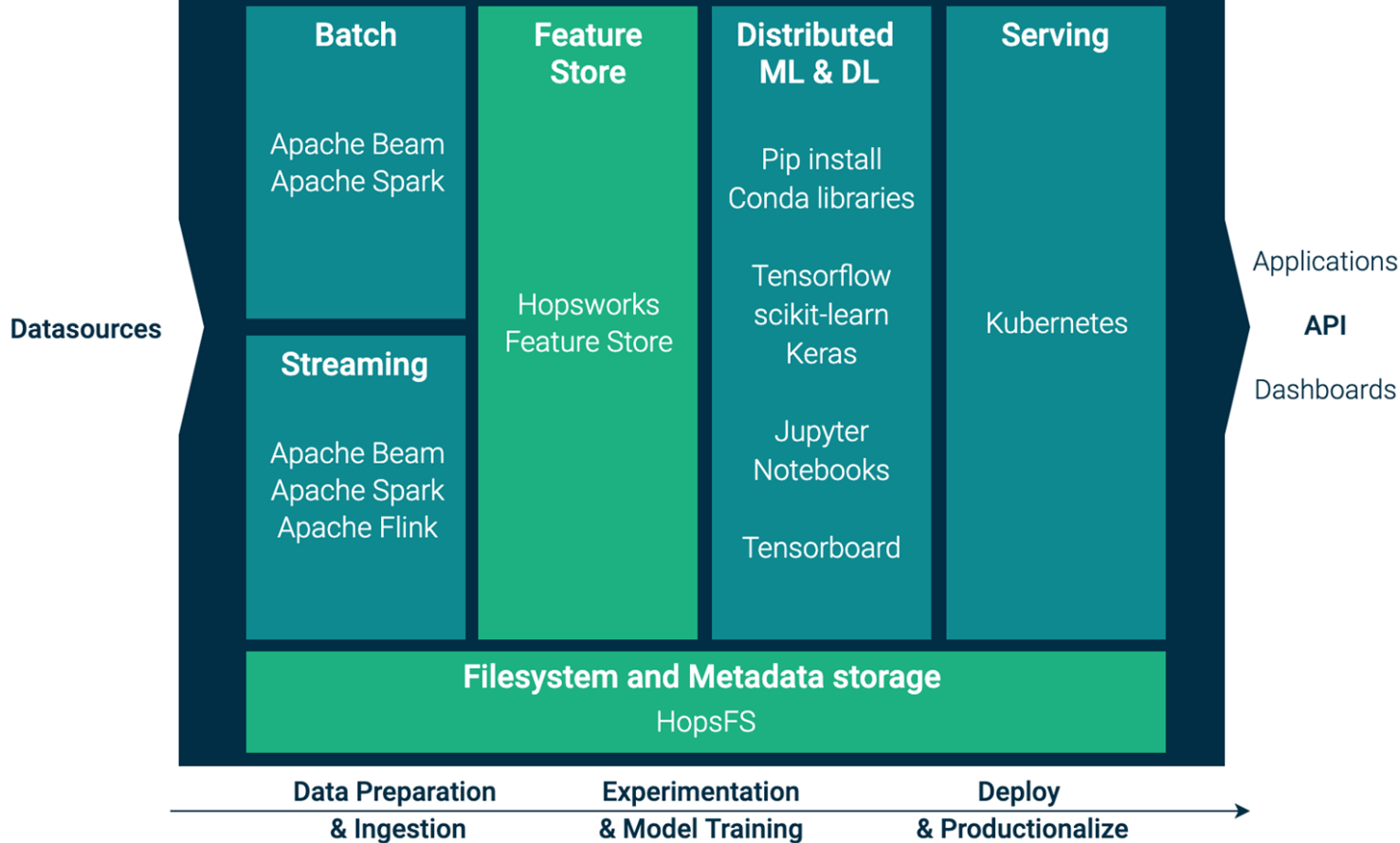
Applications

API

Dashboards



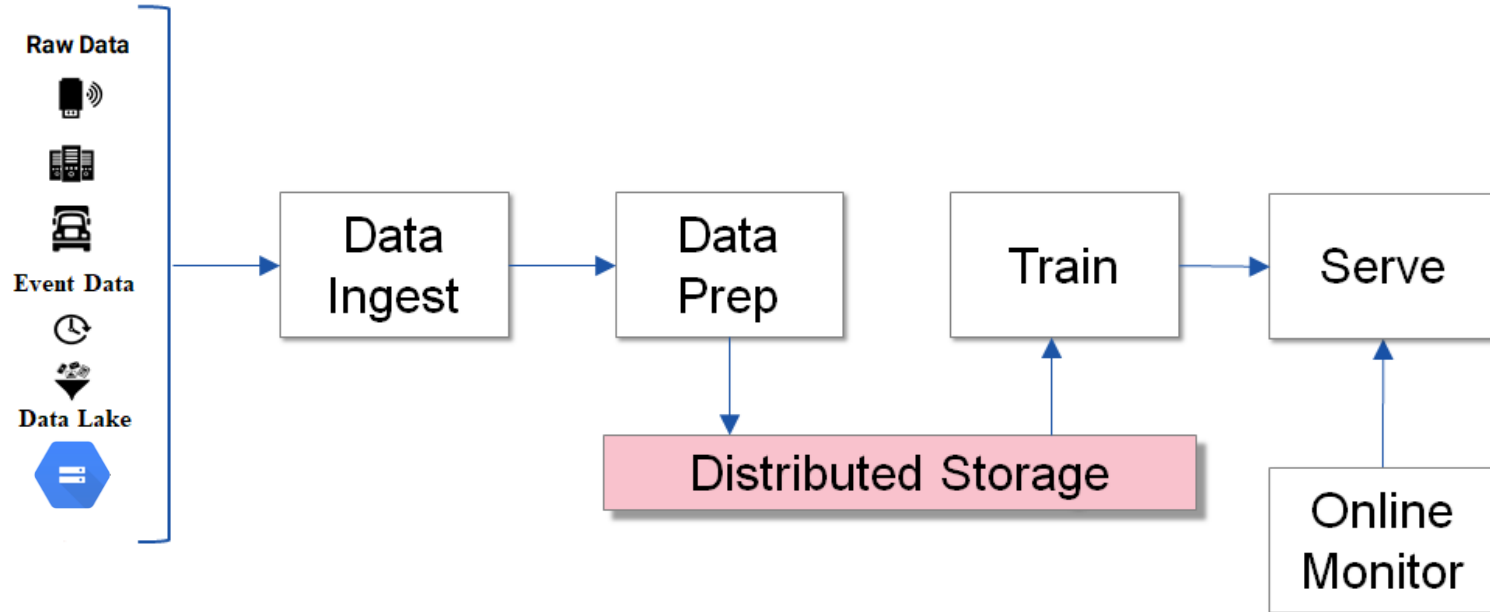
Hopsworks



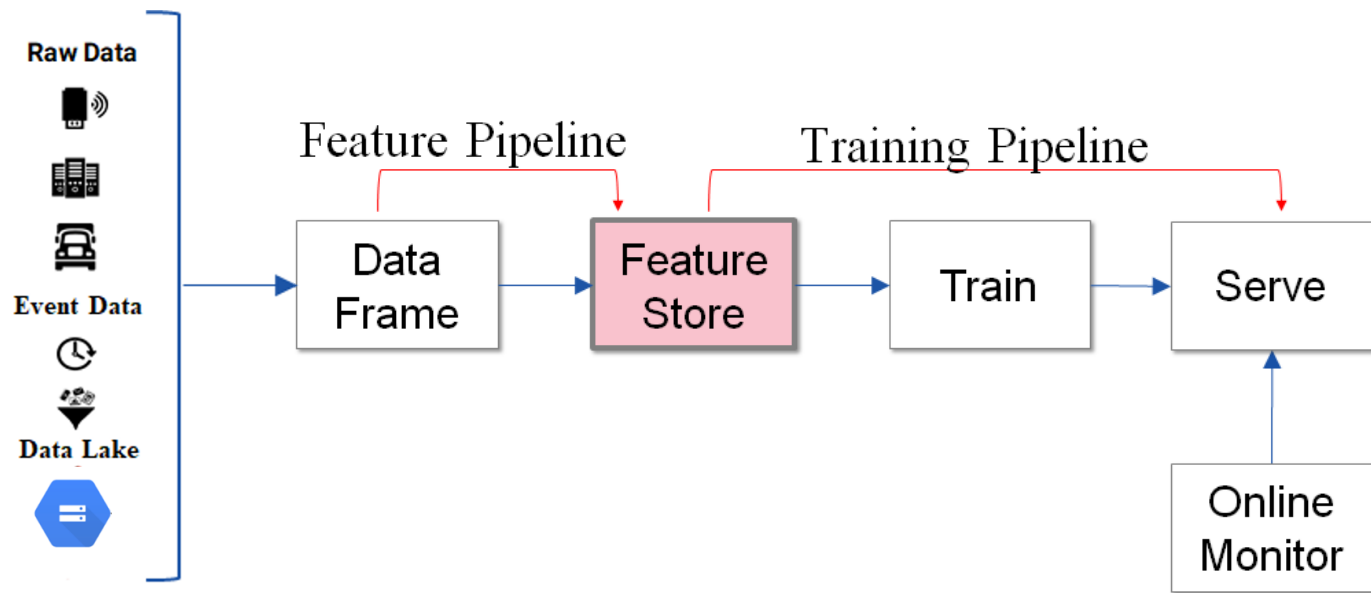
Machine Learning Pipelines

The background of the slide is a dark, atmospheric photograph. It shows a night sky filled with stars and a faint, glowing band of the Milky Way galaxy. Below the sky, a dark, silhouetted mountain range stretches across the horizon. The mountains and the sky are reflected in a calm body of water in the foreground, creating a symmetrical effect. The overall color palette is deep blues and blacks, with some lighter blue and white highlights from the stars and the Milky Way.

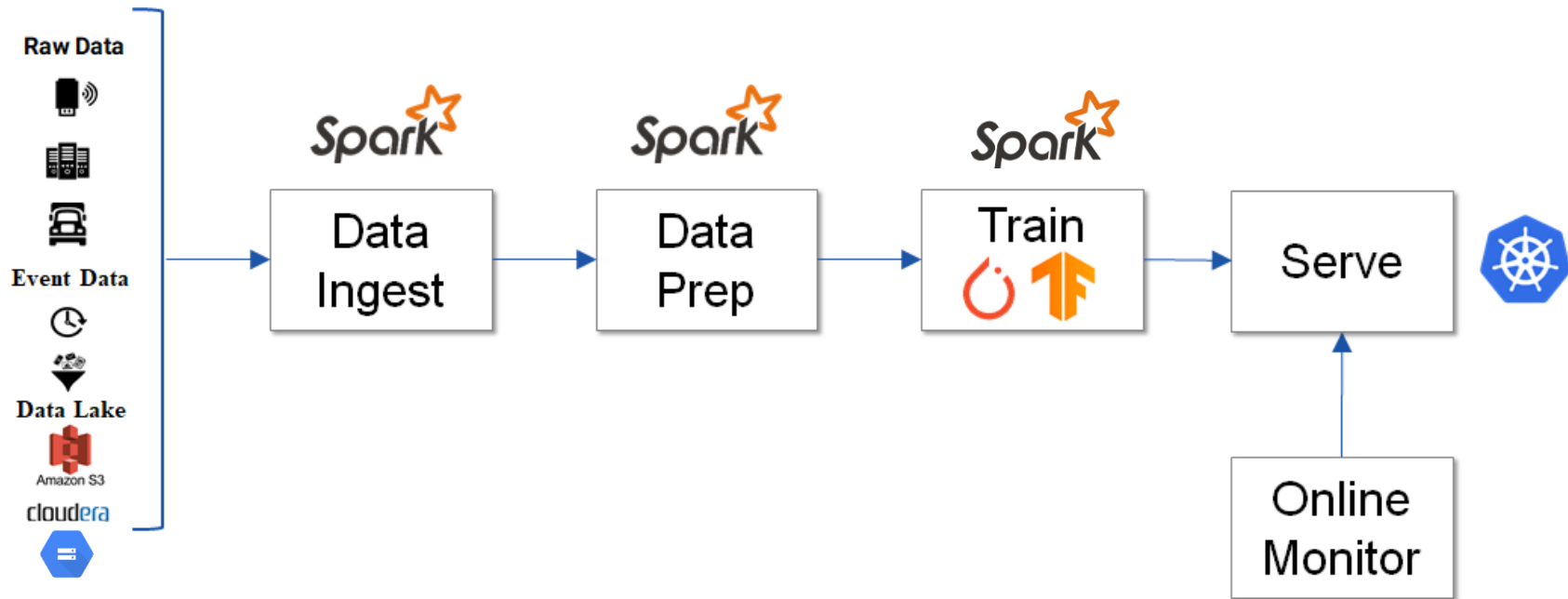
End-to-End ML Pipelines



ML Pipelines with a Feature Store



End-to-End ML Pipelines in Hopsworks



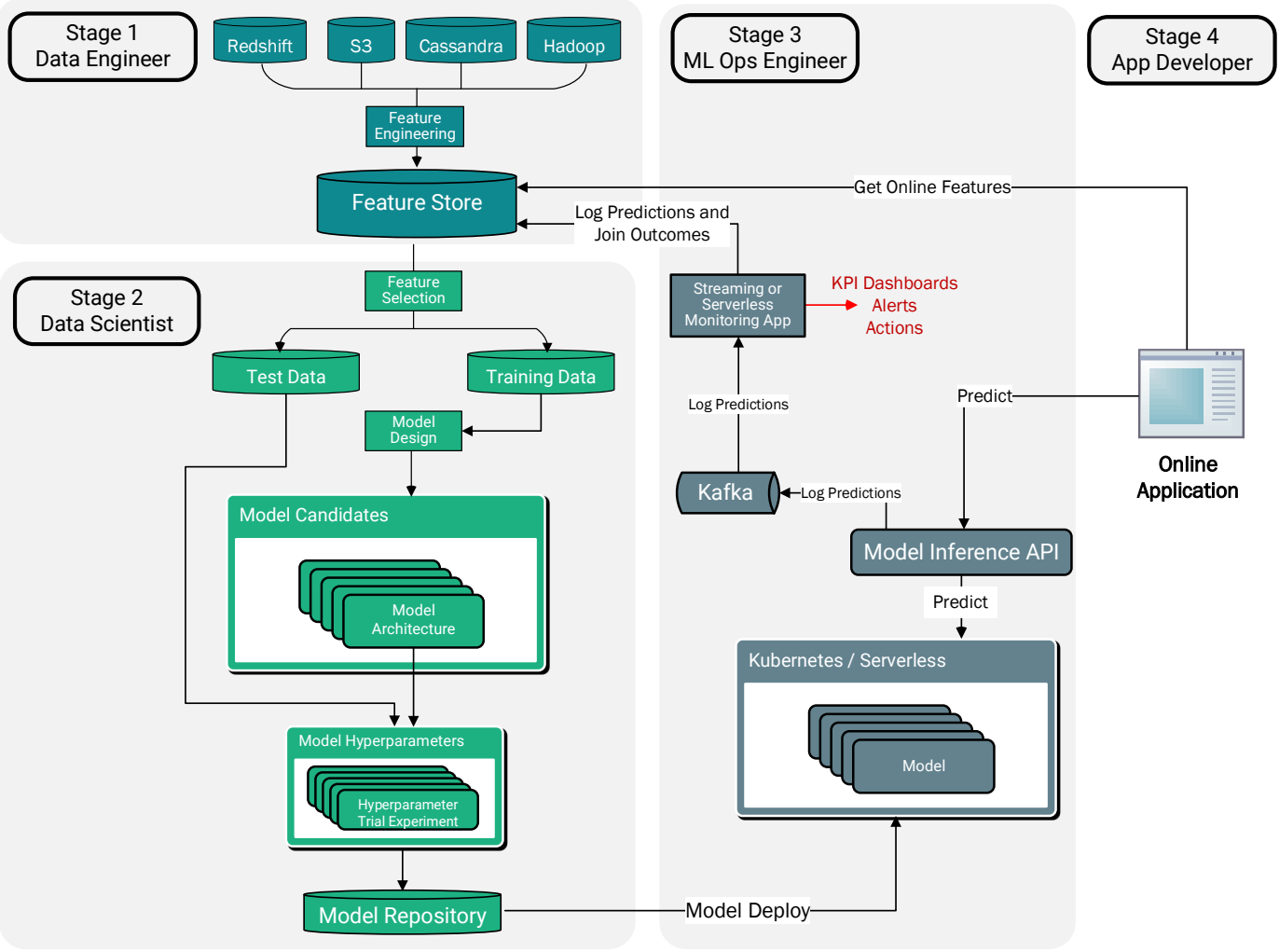
Roles in Machine Learning

Stage 1. Data Engineer

Stage 2. Data Scientist

Stage 3. ML Ops Engineer

Stage 4. App Developer

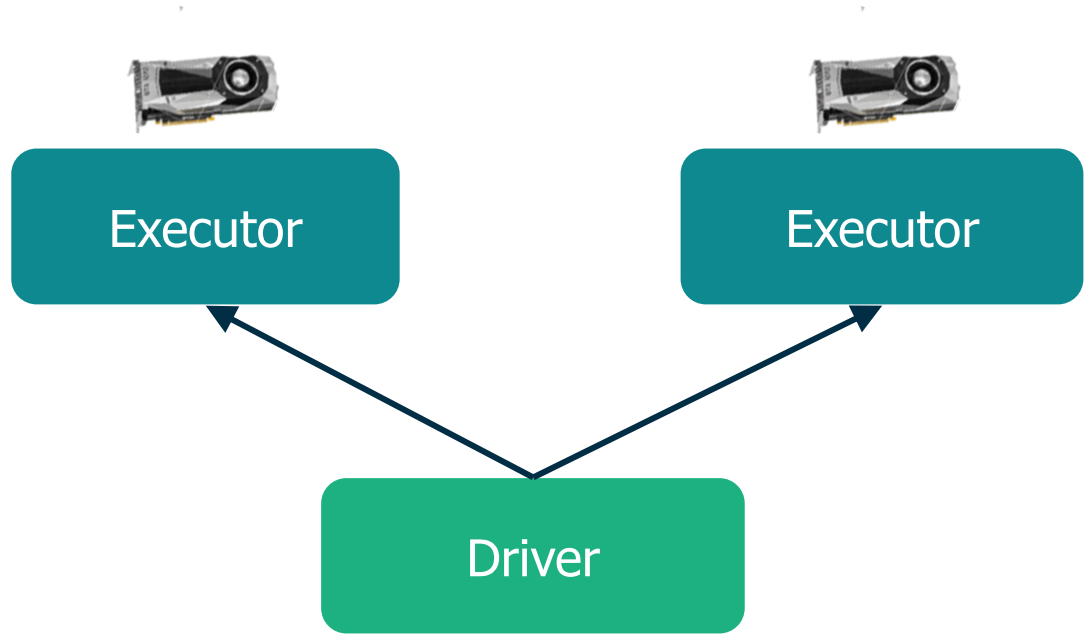


Running TensorFlow/Keras/PyTorch Apps in PySpark

Warning: micro-exposure to PySpark may cure you of distributed programming phobia

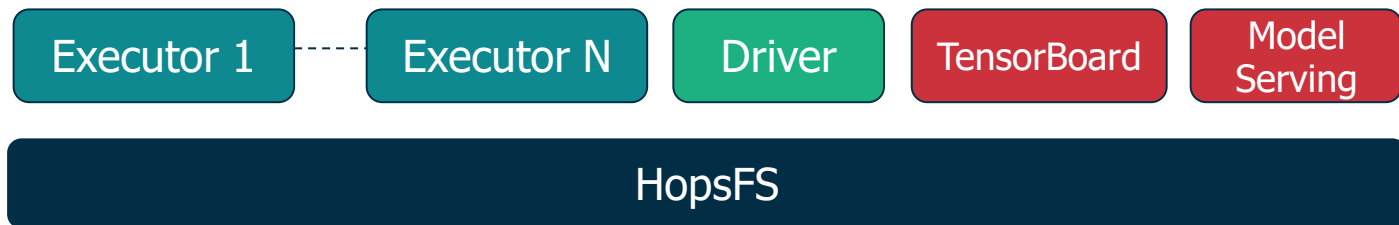
GPU(s) in PySpark Executor, Driver coordinates

PySpark makes it easier to write TensorFlow/Keras/PyTorch code that can either be run on a single GPU or scale to run on lots of GPUS for Parallel Experiments or Distributed Training.



Need Distributed Filesystem for Coordination

- Training/Test Datasets
- Model checkpoints, Trained Models
- Experiment run data
- Provenance data
- Application logs



PySpark Hello World

```
def executor():  
    print("Hello from GPU")  
  
from hops import experiment  
experiment.launch(executor)
```


PySpark – Hello World

In []:

```
def executor():  
    print("Hello from GPU")
```

In []:

```
from hops import experiment  
experiment.launch(executor)
```

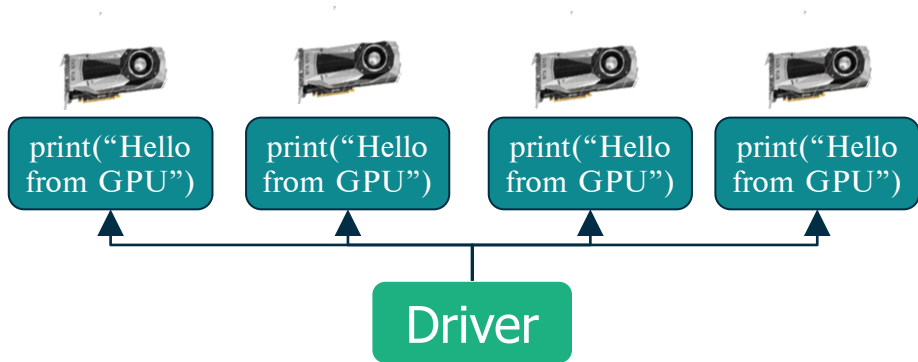
Executor
print("Hello from
GPU")

*

1

Driver
experiment.launch(..)

Leave code unchanged, but configure 4 Executors



Start

Experiment ⓘ Parallel Experiments ⓘ Distributed Training ⓘ

Hours to shutdown ⓘ 6 ▼

Driver memory (MB) ⓘ 2048

Distribution strategy ⓘ COLLECTIVE_ALL_REDUCE ▼

Workers ⓘ 4

Executor memory (MB) ⓘ 4096

Number GPUs per worker ⓘ 1

Driver with 4 Executors

In []:

```
def executor():  
    print("Hello from GPU")
```

In []:

```
def executor():  
    print("Hello from GPU")
```

In []:

```
def executor():  
    print("Hello from GPU")
```

In []:

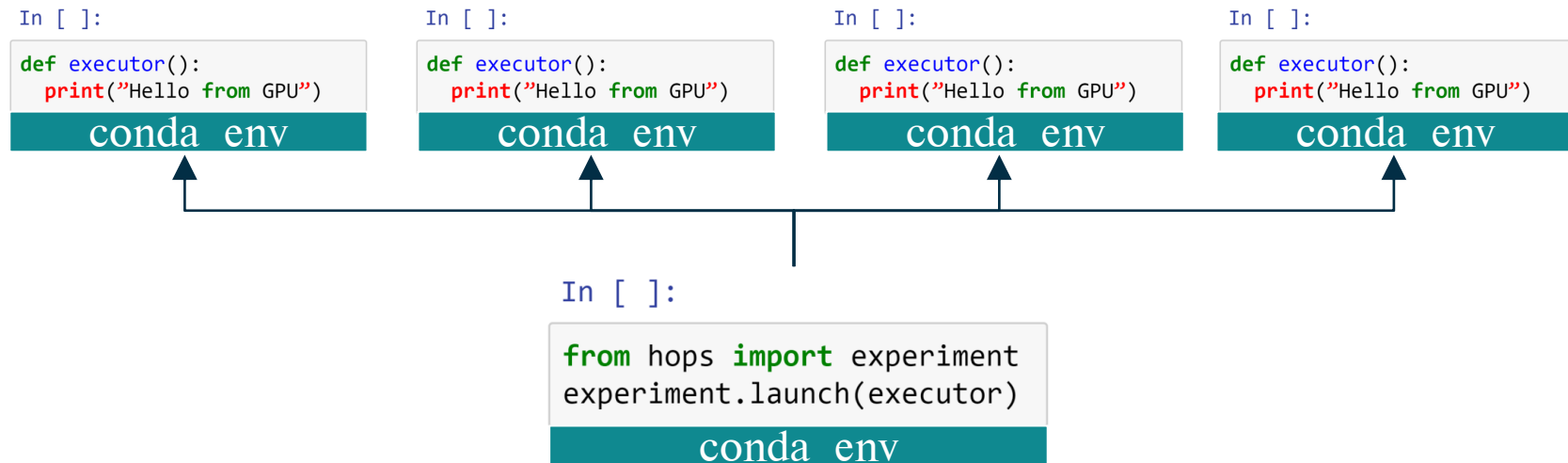
```
def executor():  
    print("Hello from GPU")
```

In []:


```
from hops import experiment  
experiment.launch(executor)
```

The diagram illustrates a driver launching four executors. A central box at the bottom contains the driver code: `In []:` followed by `from hops import experiment` and `experiment.launch(executor)`. A horizontal line extends from the `launch` method, with four vertical lines branching off to point upwards at the `executor` function boxes of four separate code snippets arranged horizontally above it. Each snippet starts with `In []:` and contains `def executor():` followed by `print("Hello from GPU")`.

Same/Replica Conda Environment on all Executors



A Conda Environment Per Project in Hopsworks

[Conda Libraries](#)[Pip Libraries](#)[Installed Python Libraries](#)[Ongoing Operations](#)[See hops python docs](#) 

Uninstall/Upgrade Python Libraries

[Export Environment](#)

Url	Library	Version	Package Manager	MachineType	Status	User-Installed▼
PyPi	hopsfacets	0.0.3	PIP	ALL	SUCCESS	Uninstall
PyPi	pandas	0.23.1	PIP	ALL	SUCCESS	Uninstall
PyPi	mmlspark	0.13	PIP	ALL	SUCCESS	Uninstall
PyPi	numpy	1.15.3	PIP	ALL	SUCCESS	Uninstall
PyPi	hops	0.6.0.1	PIP	ALL	SUCCESS	Uninstall
PyPi	pydoop	2.0a3	PIP	ALL	SUCCESS	Pre-installed
PyPi	tensorboard	1.11.0	PIP	ALL	SUCCESS	Pre-installed
PyPi	tensorflow	1.11.0	PIP	CPU	SUCCESS	Pre-installed
PyPi	tensorflow-gpu	1.11.0	PIP	GPU	SUCCESS	Pre-installed

Use Pip or Conda to install Python libraries

Conda Libraries


Pip Libraries

Installed Python Libraries

Ongoing Operations

Install Python libraries using pip in Anaconda environment

Python Version is 3.6

Search 

Installation mode

All
machines



CPU
machines



GPU
machines



Pillow-PIL

Version

0.1dev

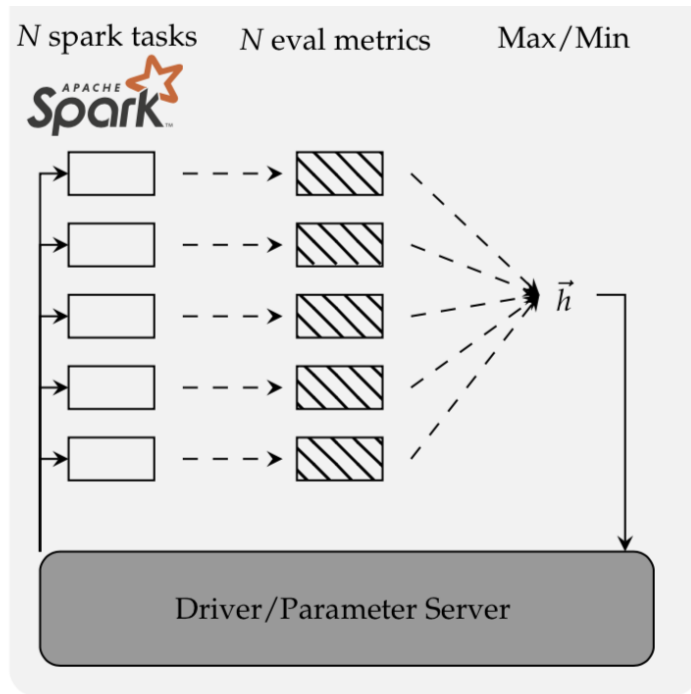
Not Installed

Install

TensorFlow Distributed Training with PySpark

```
def train():  
    # Separate shard of dataset per worker  
    # create Estimator w/ DistribStrategy  
    # as CollectiveAllReduce  
    # train model, evaluate  
    return loss  
  
# Driver code below here  
# builds TF_CONFIG and shares to workers  
from hops import experiment  
experiment.collective_allreduce(train)
```

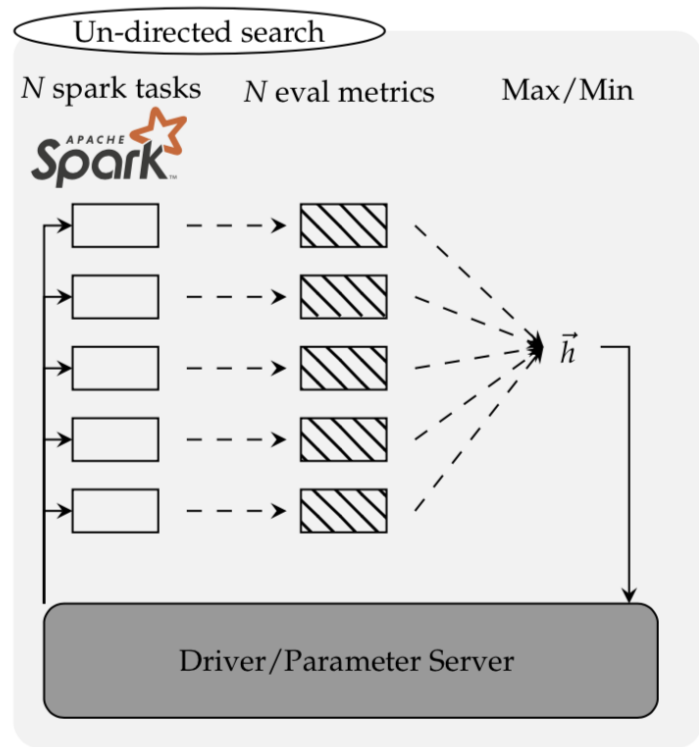
More details: <http://github.com/logicalclocks/hops-examples>



Undirected Hyperparam Search with PySpark

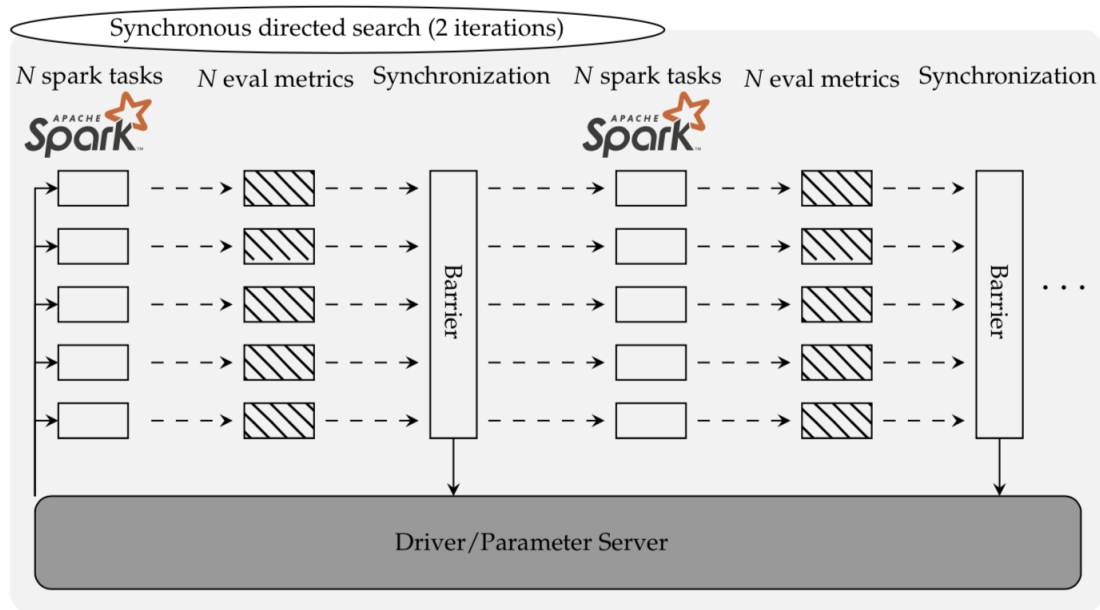
```
def train(dropout):  
    # Same dataset for all workers  
    # create model and optimizer  
    # add this worker's value of dropout  
    # train model and evaluate  
    return loss  
  
# Driver code below here  
from hops import experiment  
args={"dropout":[0.1, 0.4, 0.8]}  
experiment.grid_search(train,args)
```

More details: <http://github.com/logicalclocks/hops-examples>



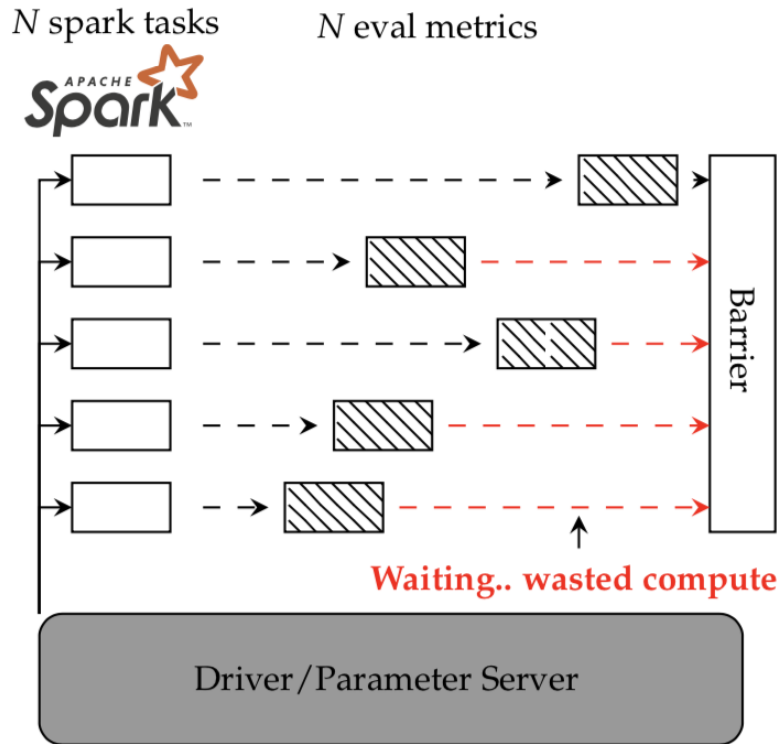
Directed Hyperparameter Search with PySpark

```
def train(dropout):  
    # Same dataset for all  
    workers  
    # create model and optimizer  
    optimizer.apply(dropout)  
    # train model and evaluate  
    return loss  
  
from hops import experiment  
args={"dropout": "0.1-0.8"}  
experiment.diff ev(train,args)
```



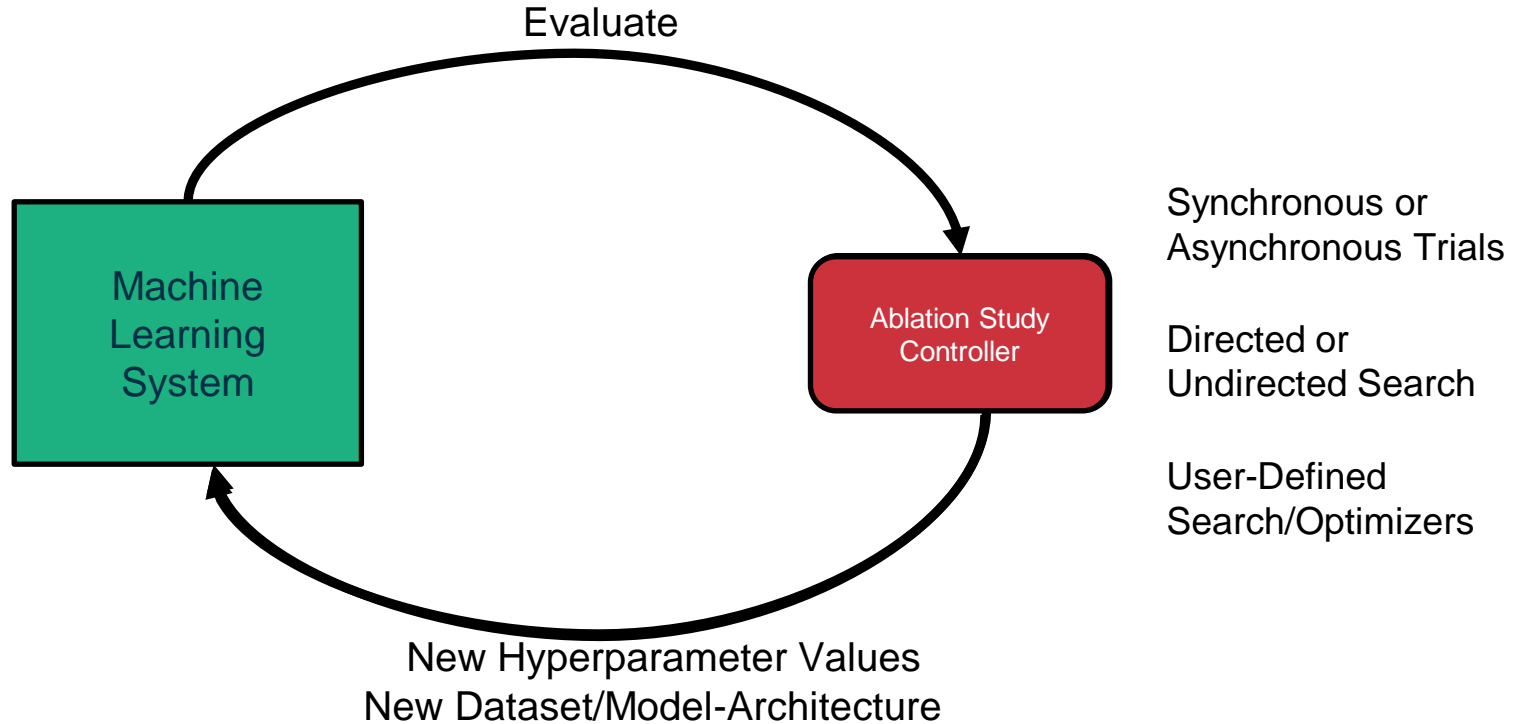
More details: <http://github.com/logicalclocks/hops-examples>

Wasted Compute!



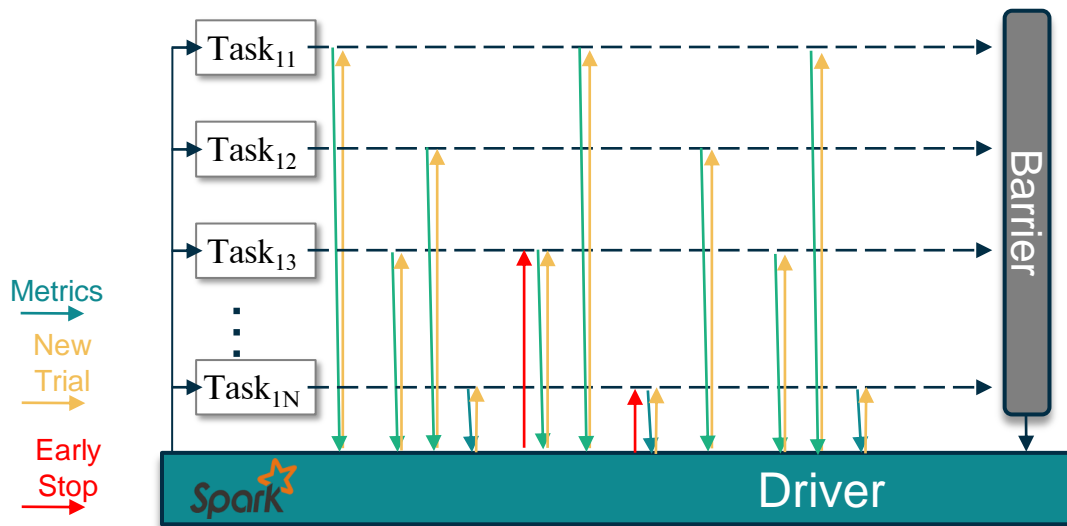
Parallel ML Trials with Maggy

Maggy: Unified Hparam Opt & Ablation Programming



Directed Hyperparameter Search with Maggy

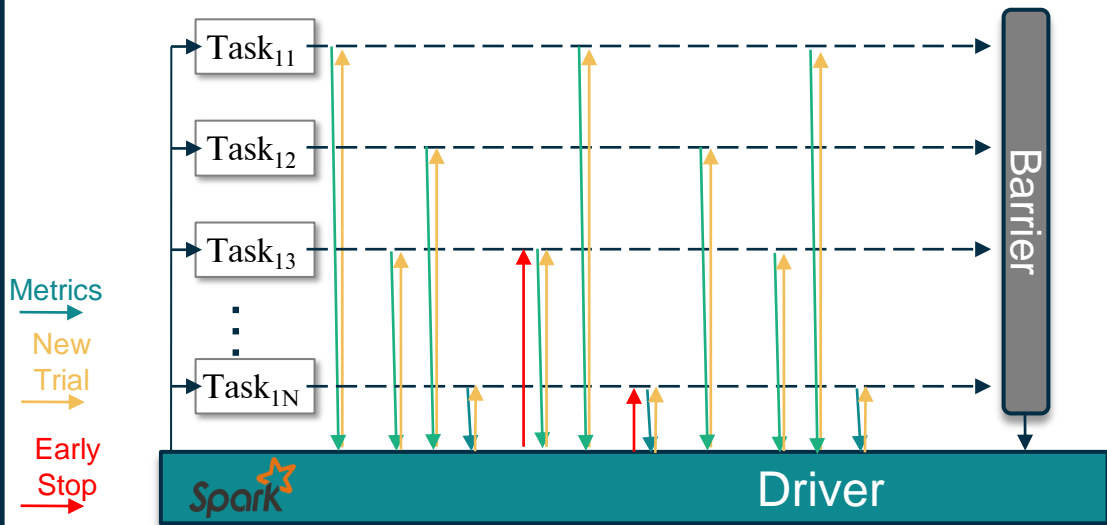
```
def train(dropout, reporter):  
    ...  
  
from maggy import experiment,  
Searchspace  
sp =  
SearchSpace(dropout=('INTEGER',  
[2, 8]))  
  
experiment.lagom(train, sp)
```



More details: <http://github.com/logicalclocks/hops-examples>

Parallel Ablation Studies with Maggy

```
def train(dataset_function,  
model_function):  
    ...  
  
from maggy import experiment  
ablation_study=...  
experiment.lagom(train,  
experiment_type='ablation',  
ablation_study=ablation_study,  
ablator='loco')
```

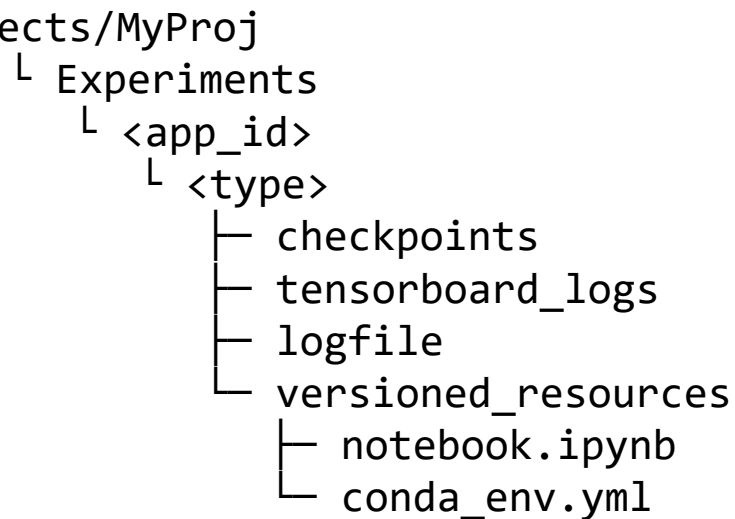


More details: <http://github.com/logicalclocks/hops-examples>

/Experiments

- Executions add entries in /Experiments:
`experiment.launch(...)`
`experiment.grid_search(...)`
`experiment.collective_allreduce(...)`
`experiment.lagom(...)`

- /Experiments contains:
 - logs (application, tensorboard)
 - executed notebook file
 - conda environment used
 - checkpoints



/Models

- Named/versioned model management for:
TensorFlow/Keras
Scikit Learn
- A **Models** dataset can be securely shared with other projects or the whole cluster
- The provenance API returns the `conda.yml` and `execution` used to train a given model

```
/Projects/MyProj
└─ Models
   └─ <name>
      └─ <version>
         ├── saved_model.pb
         ├── variables/
         └─ ...
```


That was Hopsworks

Efficiency & Performance



Feature Store

Data warehouse for ML



Distributed Deep Learning

Faster with more GPUs



HopsFS

NVMe speed with Big Data



Horizontally Scalable

Ingestion, DataPrep,
Training, Serving

Development & Operations



Development Environment

First-class Python Support



Version Everything

Code, Infrastructure, Data



Model Serving on Kubernetes

TF Serving, SkLearn



End-to-End ML Pipelines

Orchestrated by Airflow

Security & Governance



Secure Multi-Tenancy

Project-based restricted access



Encryption At-Rest, In-Motion

TLS/SSL everywhere



AI-Asset Governance

Models, experiments, data, GPUs



Data/Model/Feature Lineage

Discover/track dependencies

Acknowledgements and References

Slides and Diagrams from colleagues:

- Maggy: Moritz Meister and Sina Sheikholeslami
- Feature Store: Kim Hammar
- Beam/Flink on Hopsworks: Theofilos Kakantousis



References

- HopsFS: Scaling hierarchical file system metadata ..., USENIX FAST 2017.
- Size matters: Improving the performance of small files ..., ACM Middleware 2018.
- ePipe: Near Real-Time Polyglot Persistence of HopsFS Metadata, CCGrid, 2019.
- Hopsworks Demo, SysML 2019.

Thank you!



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GitHub 

<https://github.com/logicalclocks/hopsworks>

<https://github.com/hopshadoop/hops>